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Research on Equipment Maintenance Policy Method under Uncertain Environment

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Abstract

The application of optimal maintenance policy is investigated for minimizing the equipment breakdowns and maintenance cost. The types of equipment maintenance policy are analyzed in this article, to study the dependence of failure on equipment life. Meanwhile, it is difficult to establish an accurate failure rate prediction model due to the lack of data collection. In order to solve practical problems, equipment failure prediction model is proposed based on grey Markov model. Consider that the actual failure interval of equipments is to contribute to maintenance planning and scheduling, it is used for statistical analysis of the failure trend. Background value of GM (1, 1) model is optimized by the application of PSO aiming at getting accurate prediction curve. A case study of a open-pit mining is provided as an example to demonstrate the validity of the proposed methods. Comparison of traditional model that improved model shows the efficiency of the methods.

Keywords

Maintenance Policy; Markov Model; GM(1,1) ; PSO

Introduction

Equipment of open-pit mining industry plays an important role due to the characteristics of large-scale, high efficiency and big investment. Equipment maintenance management is an essential part of open-pit mine daily management work and maintenance policies centered on reliability can lead to effective cost reduction. Therefore, the selection of status data and the way to integrate it can affect the efficiency of the maintenance policy directly[1]. In short, maintenance can be described as a combination of all technical and administrative actions including supervision, action intended to retain or restore the system into a state in which system can perform a required function [2].

Maintenance policies can be classified into five types according to the way it deals with breakdowns and maintenance. Among them, PM policy is applied when production equipment is maintained with a significant amount of useful life remaining. But, it is difficult to identify the optimal maintenance interval by reason of the lack of historical data. This will lead to unnecessary maintenance and more maintenance cost [4]. Maintenance operations are scheduled according to performance, health indicators, or behavior of the system and focus on both real-time diagnostics and prognosis of the equipment in the CBM. Meanwhile, CBM can be feasible to obtain the exact hazard rate of a deteriorating system [7] [8]. In this paper, prediction model is a combination of GM (1, 1) and Markov model based on underlying equipment failure rate recursion evolution. The models of equipment failure rate are to find optimum equipment maintenance policies and to identify imperfect or hazardous repair, so that maintenance policy can be further investigated and improved if it needs [9]. The model helps accurately describe the equipment failure rate in different maintenance cycles during the system lifetime.

Upon obtaining the failure rates of such equipments, the first step is to conduct a statistical distribution fitting to the initial data per equipment or failure mode. Because of the lack of quality or quantity of the data, the mean percentage of failures is computed while considering that the fitted statistical distribution may not be similar to the historical data. Therefore, a common practice is to perform some adjustments in the distribution parameters based on human intelligence and the experience of the engineers [10]. Against this background, this paper deals with maintenance policy taking into account of following problems. The first of all is devoted to the equipment performance description and the assumptions. Secondly, this paper presents Grey- Markov model related to

account specific constraints maintenance opportunities. Afterwards, we use Particle Swarm Optimization (PSO) algorithm to optimize the background value of GM (1, 1) model to adjust prediction curve. Finally, the process of the maintenance policies is applied to practical examples considering various cases. And conclusions are presented.

Maintenance Policy Optimal Model

There are serious problems of equipment malfunction during operational process. So for equipment protection, how to use equipment limited fault data samples to predict the failure time is the difficulty of fault prediction. Grey model is to use less or no exact sequence to represent the system behavior characteristics. After the establishment of approximate differential equations generated by the transformation of the original series, we can get the model aimed at quantitative analysis of the system by means of incomplete information. In order to achieve these objectives, we combine with the GM (1, 1) and Markov model to solve.

In the actual problem, the exact value of transition probabilities gray zone $p_{ij}(\Theta)$ is difficult to determine because of the lack of information. When the transition probability matrix is gray matrix, the elements in the whitening matrix $\tilde{P}(\Theta) = [\tilde{P}_{ij}(\Theta)]$ meet the following requirements:

(1) $\tilde{P}_{ij}(\Theta) \geq 0; i, j \in I$。

(2) $\sum_{j \in I} \tilde{P}_{ij}(\Theta) = 1; i \in I$。

The initial distribution of finite-state gray Markov chain can be expressed as:

$$P^T(0) = (p_1, p_2, \cdots, p_n) \tag{1}$$

transition probability matrix can be expressed as:

$$\tilde{P}(\Theta) = [\tilde{P}_{ij}(\Theta)] \tag{2}$$

S distribution of the system can be expressed as:

$$P^T(s) = P^T(0)P^s(\Theta) \tag{3}$$

If initial distribution system and the transition probability matrix are known, we can make predictions of the system distribution at any time in the future .

Set the original data as $x^{(0)}(k)(k = 1,2,\cdots,p)$, and $\hat{y}(k)$ as the predicted value of the raw data obtained at the time k. Curve $\hat{y}(k)$ reflects the trend of the original data column. If non-stationary random sequence $x^{(0)}(k)$ according to Markov chain which is divided into "n" states, the expression of any state Θ_i is:

$$\Theta_i = [\tilde{\Theta}_{1i}, \tilde{\Theta}_{2i}], \ \tilde{\Theta}_i \in \Theta_i, \ \tilde{\Theta}_{1i} = \hat{y}(k) + A_i, \ \tilde{\Theta}_{2i} = \hat{y}(k) + B_i; \ i = 1,2,\cdots,n$$

Since $\hat{y}(k)$ is the time function of k, the original gray $\tilde{\Theta}_{1i}, \tilde{\Theta}_{2i}$ also is time-varying.

If $M_{ij}(m)$ is raw data sample by state Θ_i through m step transition to the state Θ_j, M_i is raw data samples in a state of Θ_i , we call $p_{ij}(m)$ state transition probability.

$$p_{ij}(m) = \frac{M_{ij}(m)}{M_i}; \ i = 1,2,\cdots,n \tag{4}$$

In practice, usually only one step probability matrix can be considered. If prediction object is at state Θ_k, it is difficult to determine the future status of the steering when there are two or more identical or similar probabilities in the row k of P. At this time, We need to look into two or n-step transition matrix P^2 or P^2 (n≥3).

Case Study

We can interpret the results of the traditional model and the improved model as in the following sections. As

shown in Table 1, we obtain the prediction model based on actual data through gray prediction method. We set the initial background value as $P_0 = (0.5, 0.5, \cdots, 0.5)$, $[L_d, U_d] = [0,1]$, $c_1 = c_2 = 2$. Using MATLAB and GM (1,1) model to predict the two sets of data, model is obtained in which $a = 3.5305$, $b = 0.038$. Fig. 1 is the predicted curve. Then the background value is optimized by PSO the number of iterations of 1000 to get a new model in which $a = 3.7370$, $b = -0.0341$. The differences of residual error and relative error between the traditional model and improved model are statistically significant.

TABLE 1 PART OF ACTUAL DATA AND MODEL PREDICTIONS

Serial number	Actual value	Predicted value		Residual error		Relative error	
		Traditional model	Improved model	Traditional model	Improved model	Traditional model	Improved model
1	4.4	4.4	4.4	0	0	0.0000	0.0000
2	4.2	3.9635	3.954	0.2356	0.2462	0.0594	0.0623
3	3.8	4.1012	4.0911	-0.3012	-0.2897	0.0734	0.0708
4	4.2	4.2437	4.233	-0.0437	-0.0303	0.0103	0.0072
5	3.9	4.3911	4.3797	-0.4911	-0.4797	0.1118	0.1095
6	4.3	4.5436	4.5316	-0.2436	-0.2316	0.0536	0.0511
7	4.9	4.7014	4.6888	0.1986	0.2112	0.0422	0.0450
8	5.2	4.8648	4.8514	0.3352	0.3486	0.0689	0.0719
9	4.5	5.0337	5.0196	-0.5337	-0.5196	0.1060	0.1035
10	5.4	5.2086	5.1936	0.1914	0.2064	0.0367	0.0397

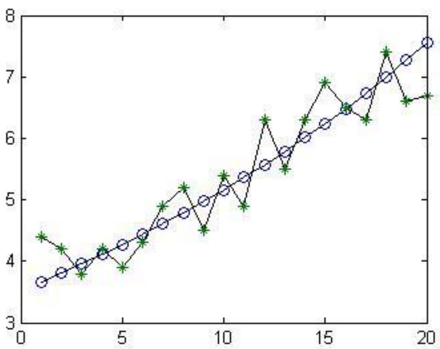

FIG.1 FORECAST GRAPH

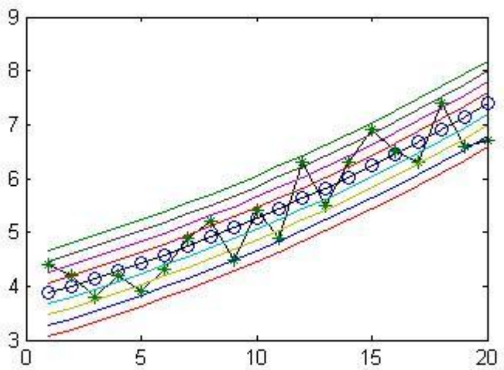

FIG.2 FORECAST GRAY INTERVAL DIVISION FIGURE

It can be drawn that the data through the transformation sequence become smooth, resulting in a good prediction. The modeling accuracy and posterior mean variance has been greatly improved by improved model.

Gray interval division is performed according to the optimized curve as shown in Fig.2. We can determine transition probability matrix by the number of state points. Furthermore, maintenance policy can be determined at the future time.

Conclusions

As indicated from the analyzed results of the above application, the actual data of failure interval are used to calculate the failure distribution of equipment. The smoothness of the sequence was improved through the optimization of the original GM (1, 1) model. The prediction accuracy of failure interval was significant. Besides, this paper just focuses on the failure distribution analysis methods. Therefore, analysis of multiple component states and cost-effective configuration optimization with the aim of mitigating in unreliable equipment is needed for further study.

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REFERENCES

[1] Dogramaci, Ali and N. M. Fraiman, "Replacement Decisions with Maintenance Under Uncertainty: An Imbedded Optimal Control Model", Operations research, vol. 52, no. 5, pp. 785-794, 2004.

[2] Khoury, E., Deloux, E, Grall, A, Bérenguer, C, Khoury, E, Deloux, E and Bérenguer, C, "On the Use of Time-Limited Information for Maintenance Decision Support: A Predictive Approach under Maintenance Constraints", Mathematical Problems in Engineering, vol. 11, no. 5, pp. 497-504, 2013.

[3] Swanson, Laura, "Linking maintenance strategies to performance", International Journal of Production Economics, vol. 70, no. 3, pp. 237-244, 2001.

[4] Ding, Siew Hong and S. Kamaruddin, "Maintenance policy optimization—literature review and directions", International Journal of Advanced Manufacturing Technology, vol. 76, pp. 1263-1283, 2015.

[5] Qian, Xinbo and Y. Wu, "Dynamic Control-limit Policy of Condition based Maintenance for the Hydroelectricity Generating Unit", International Journal of Security & Its Applications, 2014.

[6] Wang, Ling, J. Chu and J. Wu, "Selection of optimum maintenance strategies based on a fuzzy analytic hierarchy process", International Journal of Production Economics, vol. 107, no. 1, pp. 151-163, 2007.

[7] Safari, Ehram, S. J. Sadjadi and K. Shahanaghi, "Scheduling flowshops with condition-based maintenance constraint to minimize expected makespan", International Journal of Advanced Manufacturing Technology, vol. 46, no. 5-8, pp. 757-767, 2010.

[8] Ennis, M., Makis, V, Jardine, A K S, Banjevic, D and Braticevic, D, "A decision optimization model for condition-based maintenance", Journal of Quality in Maintenance Engineering, vol. 4, no. 2, pp. 115-121, 1998.

[9] Baker and Rose D, "Data-Based Modeling of the Failure Rate of Repairable Equipment", Lifetime Data Analysis, vol. 7, no. 1, pp. 65-83, 2001.

[10] Kibria, Ahmed, K. K. Castillo-Villar and H. Millwater, "Minimizing the Discrepancy between Simulated and Historical Failures in Turbine Engines: A Simulation-Based Optimization Method", Mathematical Problems in Engineering, 2015.